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Markov modeling and analysis of multi-stage manufacturing systems with remote quality information feedback ☆

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ABSTRACT

Modeling and analysis of multi-stage manufacturing systems (MMSs) for product quality propagation have attracted a great deal of attention recently. Due to cost and resources constraints, MMSs do not always have ubiquitous inspection, and MMSs with remote quality information feedback (RQIF, i.e., quality inspection operation is conducted at the end of the production line) are widely applied. This paper develops a Markov model to analyze quality propagation in MMSs with RQIF. Analytical expressions of the final product quality are derived and the monotonicity properties are investigated. A quality bottleneck identification method is explored based on the proposed Markov model. The results of case study demonstrate the effectiveness of the proposed model.

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1. Introduction

Most complex manufacturing systems involve a large number of stages. As workpieces move through these stages, the variations of product quality are usually introduced and propagated. The variations of the final product quality are the accumulation of variations from all stages. Therefore, it is significantly important to investigate the product quality propagation in multi-stage manufacturing systems (MMSs).

Modeling and analysis of MMSs for quality improvement have received intensive investigation. Recent quantitative modeling methods can be roughly classified as data-driven (applying statistical approaches based on measurement data) and analytical (applying physical approaches based on engineering knowledge) methods. Data-driven methods focus on investigating patterns in the massive historical quality dataset to model the relationships between the product quality and manufacturing systems and thus do not require a comprehensive prior knowledge of the systems. Some authors employ data-driven auto-regression (AR) models to describe the quality propagation (Agrawal, Lawless, & Mackay, 1999; Lawless, Mackay, & Robinson, 1999). The parameters of their AR(1) models are estimated based on product measurements. Some authors develop data-driven modeling methods based on the analysis of the linear space spanned by the eigenvectors of the covariance matrix of the quality measurements (Jin & Zhou, 2006; Johnson & Wichern, 2002). Mondal, Maiti, and Ray (2013) combined statistical regression, Taylor series expansion and a variation model to investigate the robustness of MMSs.

Different from data-driven models, analytical models employ off-line analysis of MMSs based on fundamental physical laws. One of the most popular analytical models used for quality improvement is the state space model, first developed by Jin and Shi (1999) for two-dimensional assembly systems. This model directly links engineering knowledge of variation sources with product measurement data. Since then, it is further investigated in three-dimensional assembly systems (Camelio, Hu, & Ceglarek, 2004; Ding, Ceglarek, & Shi, 2002a; Huang, Lin, Bezdecny, Kong, & Ceglarek, 2007; Huang, Lin, Kong, & Ceglarek, 2007; Loose, Chen, & Zhou, 2009; Zhou, Qiang, & Zhou, 2012). However, these models could not be applied in the machining systems directly since the fundamental physical laws of quality propagation are quite different for assembly and machining systems (Du, Yao, Huang, & Wang, 2015). Therefore, some authors (Abellan-Nebot, Liu, Subirón, & Shi, 2012; Djurdjanovic & Ni, 2001, 2003, 2006; Du, Yao, & Huang, 2014, 2015; Huang & Shi, 2004a, 2004b; Huang, Shi, & Yuan, 2003; Loose, Zhou, & Ceglarek, 2007; Loose, Zhou, Zhou, & Ceglarek, 2010; Wang, Huang, & Katz, 2005; Zhou, Chen, & Shi, 2004; Zhou, Huang, & Shi, 2003) investigate the variation propagation for machining systems by applying the

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Nomenclature

M_i	the ith stage in MMSs
M'_i	the stage merged by the first i stages in MMSs
g_i	M_i or M'_i is producing a good product
d_i	M_i or M'_i is producing a defective product
$g_i g_{i+1}$	M_i or M'_i is producing a good product and M_{i+1} is also producing a good product
$g_i d_{i+1}$	M_i or M'_i is producing a good product and M_{i+1} is producing a defective product
$d_i g_{i+1}$	M_i or M'_i is producing a defective product and M_{i+1} is producing a good product
$d_i d_{i+1}$	M_i or M'_i is producing a defective product and M_{i+1} is also producing a defective product
P	the probability of the system in one certain steady state
α_1	the probability for M_1 to transit from state g_1 to state d_1
β_1	the probability for M_1 to transit from state d_1 to state g_1
α'_i	the probability for M'_i to transit from state g_i to state $d_i (i \geqslant 2)$
β'_i	the probability for M'_i to transit from state g_i to state $g_i (i \geqslant 2)$
γ_i	when the coming part is good, the probability for M_i to transit from state g_i to state d_i
μ_i	when the coming part is good, the probability for M_i to transit from state d_i to state g_i
η_i	when the coming part is defective, the probability for M_i to transit from state g_i to state d_i
θ_i	when the coming part is defective, the probability for M_i to transit from state d_i to state g_i
λ'_i	quality failure probability for ith stage in general Markov model
μ'_i	quality repair probability for ith stage in general Markov model
λ''_i	quality failure probability without repair for ith stage in quality flow model
v''_i	quality failure probability with repair for ith stage in quality flow model
μ''_i	quality repair probability for ith stage in quality flow model
$X_{i,t}$	the matrix of state probabilities at time t for the system with i stages
X_i	the matrix of steady-state probabilities for the system with i stages
A_i	the matrix of state transition probabilities for the system with i stages
S_{γ_k}	the sensitivity of $P(g_k)$ with respect to γ_k
S_{μ_k}	the sensitivity of $P(g_k)$ with respect to μ_k
S_{η_k}	the sensitivity of $P(g_k)$ with respect to η_k
S_{θ_k}	the sensitivity of $P(g_k)$ with respect to θ_k

state space model. Detailed descriptions of existing research on the state space model are provided in a monograph (Shi, 2006) and a survey (Shi & Zhou, 2009). However, analysis of complex systems using the state space model based on physical laws is often intractable (Shi & Zhou, 2009), and such analysis either relies on complicated kinematics model of manufacturing systems, or is only applicable to deal with dimensional errors and the application area is limited (Ju, Li, Xiao, & Arinez, 2013; Ju, Li, Xiao, Huang, & Biller, 2014).

In another research line, Markov model has been widely used as analytical tool to investigate the interactions between manufacturing system design and product quality. Inman, Blumenfeld, Huang, and Li (2003) pointed out that product quality and manufacturing system design are tightly coupled. They reviewed the related literature and empirical evidence to show that manufacturing system design has a significant impact on product quality. Since then, the coupling between manufacturing system design and product quality has received more and more research attention. Kim and Gershwin (2005) developed a Markov model for machines with both quality and operational failures, and identified important differences between types of quality failures. Li and Huang (2007) applied a Markov model to evaluate quality performance and derived some closed expressions to calculate good part probability. Kim and Gershwin (2008) proposed analytical and computational methods using Markov model to evaluate three cases of long manufacturing lines with quality and operational failures. Li, Blumenfeld, and Marin (2008) investigated the impact of manufacturing system design on product quality through a case study at an automotive paint shop and introduce the notion of quality robustness. Wang, Li, Arinez, and Biller (2010) derived a closed formula to quantify the probability of producing a good part using a Markov chain model and investigated nonmonotonic properties of manufacturing systems. Colledani and Tolio (2011) proposed an analytical method for the joint design of quality and manufacturing parameters. Wang, Li, Arinez, and Biller (2012) introduced some indicators for identifying the quality improvability and bottleneck sequence based on a Markov model. Ioannidis (2013) used a Markov model to investigate joint production and quality control in manufacturing systems with random demand. Wang, Li, Arinez, and Biller (2013) developed a Markov model to analyze product quality in manufacturing systems with batch productions and a notation of quality bottleneck transaction was introduced to describe the state transition that has the largest impact on quality. Zhao and Li (2014) developed Markov analytical models to characterize a furniture assembly system and lot size analysis and bottleneck analysis were carried out. The related literature are reviewed and new directions are provided by Inman, Blumenfeld, Huang, and Li (2013).

In spite of above effort, the current research work based on Markov models assume that each stage of a manufacturing system is independent, in other words, the product quality propagation does not considered in their systems. Ju et al. (2013, 2014) developed quality flow models to analyze product quality propagation and to identify the quality bottleneck for automotive paint system and battery manufacturing system respectively. The applicability of their models is demonstrated using case study. However, their quality flow models are based on assumption that the manufacturing system has ubiquitous inspection, namely, every stage has an inspection station. Due to cost and resources constraints in reality, it is not always possible to measure outputs and set up inspection station in every stage in a manufacturing system. A manufacturing system with remote quality information feedback (RQIF) is a representation of situations where most but not all operations are reliable in terms of quality and where the product defects are only inspected and identified at the end of the production line (see Fig. 1). This is not desirable, but it is often unavoidable and applied in reality (Kim & Gershwin, 2008; Montgomery, 2009).

Manufacturing systems with RQIF are often applied. Ding, Ceglarek, and Shi (2002b) described a multistage assembly system including three assembly stages and one measurement station at the end of the assembly line. Zantek, Wright, and Plante (2002,

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